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An Intelligent Learning Framework for Predictive Modelling in AI-Driven Career Guidance

Ms. A. Kannammal[1], A. Andrew Selvakumar[2], S. Gopika[3], P. Aruna[4], S. A. Manoj Kumar[5]
[1]Professor/HOD/IT, Jayalakshmi Institute of Technology, Anna University, Thoppur, Dharmapuri, 636352, Tamil Nadu, India.
[2,3,4,5]UG, Computer Science and Engineering, Jayalakshmi Institute of Technology, Anna University, Thoppur, Dharmapuri, 636352, Tamil Nadu, India.
Emails: *kannammal.cse1@gmail.com[1], andrewselvakumar07@gmail.com[2], gopikasiddhuraj@gmail.com[3], , aruna301089@gmail.com[4], manojkumarashokan39@gmail.com5*

Abstract
Traditional career guidance systems often rely on static keyword matching and rigid rule-based filters, which are limited in their ability to capture the nuanced aspirations, evolving skill sets, contextual preferences, and emotional states of users. Such approaches often produce generic recommendations that lack personalization and adaptability. To address these limitations, this paper proposes an Intelligent Learning Framework for predictive modelling in AI-driven career guidance, designed to deliver highly personalized, context-aware, and continuously adaptive career recommendations. The proposed framework adopts a hybrid multi-agent architecture that integrates multiple intelligent components to enhance decision-making. Semantic understanding is achieved through Sentence-BERT (SBERT) combined with Cosine Similarity, enabling deep contextual matching between user profiles and career domains. A Rule-Based Engine is incorporated to enforce logical constraints, domain knowledge, and eligibility criteria, ensuring the validity and reliability of recommendations. Furthermore, Reinforcement Learning using Q-Learning is employed to dynamically refine the system's predictions based on user feedback, interaction patterns, and long-term learning objectives. To further enhance user engagement, the system incorporates emotion-aware interaction using VADER Sentiment Analysis, allowing it to interpret user sentiments from textual inputs and adjust recommendations accordingly. This ensures a more empathetic and user-centric guidance experience. The system is implemented using a Flask-based backend integrated with a MySQL database, supporting scalable deployment, efficient data handling, and modular system design. Additionally, the framework emphasizes explainability by providing transparent reasoning behind each recommendation, thereby improving user trust and interpretability. The model considers multiple input dimensions, including user interests, academic background, skills, and preferences, to generate holistic career recommendations. Experimental results show that the proposed hybrid approach outperforms traditional systems in accuracy, adaptability, and user satisfaction, achieving a Top-3 Hit Rate of 90.5%. The integration of Q-Learning enables continuous improvement by adapting to user feedback and evolving trends. Overall, the framework is robust, scalable, and suitable for real-world deployment in educational and career guidance platforms.

Keywords: *AI-Driven Career Guidance, Multi-Agent Architecture, Predictive Modelling, Reinforcement Learning, Sentence-BERT (SBERT).*

1. Introduction
In today's rapidly evolving digital and economic landscape, effective career decision-making demands intelligent systems capable of analyzing complex, dynamic, and continuously changing data. With the proliferation of diverse career opportunities and interdisciplinary domains, individuals often struggle to align their interests, skills, and academic backgrounds with suitable career paths. This challenge is particularly pronounced in developing nations such as India, where the student-to-counsellor ratio is critically low—approximately 1:3,000 compared to the global standard of 1:250 [1], [2]. This significant gap highlights the urgent need for scalable, automated, and intelligent career guidance

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solutions. Traditional recommendation and career guidance systems are largely static, relying on keyword-based matching techniques and predefined rule-based filters. While these methods are simple and interpretable, they lack contextual understanding and adaptability. Keyword-based approaches fail to capture semantic relationships between user inputs and career domains, often resulting in irrelevant or superficial recommendations. Similarly, rule-based systems, although transparent and deterministic, are inherently rigid and unable to adapt to evolving user preferences or emerging career trends. Moreover, these systems often fail to incorporate real-time feedback and multi-dimensional user data, limiting their ability to provide personalized and evolving career guidance. To address these limitations, this paper proposes an Intelligent Learning Framework for Predictive Modelling of Real-Time Data, built upon a hybrid multi-agent AI architecture. The primary objectives of the proposed system are as follows:

- To transcend simple keyword matching by leveraging Sentence-BERT (SBERT) for deep semantic understanding of user profiles and career descriptions, enabling context-aware matching.
- To incorporate deterministic and explainable filtering through a Rule-Based Reasoning Engine that enforces domain-specific eligibility criteria and logical constraints.
- To enable dynamic personalization and continuous adaptation using a Reinforcement Learning (Q-Learning) layer that refines recommendation strategies based on explicit user feedback and interaction history.
- To enhance user engagement and trust by integrating VADER Sentiment Analysis for emotion-aware interaction, along with a Knowledge Graph to provide visual and interpretable explanations of recommendations.

The proposed system adopts a collaborative multi-agent approach, where each component contributes to a specific aspect of the decision-making process, resulting in a cohesive and intelligent recommendation pipeline. The framework is capable of processing multi-dimensional user data, including interests, skills, academic performance, and behavioral inputs, to generate holistic and relevant career suggestions.

2. Literature Review

The landscape of career guidance has undergone a significant transformation with the advent of artificial intelligence, moving beyond traditional counselling methods toward more personalized, data-driven approaches. Modern systems increasingly aim to leverage machine learning, natural language processing, and user modelling to provide tailored career recommendations. This section critically reviews existing research contributions and industry platforms, highlighting their strengths while identifying key limitations that motivate the proposed framework.

2.1. Review of Academic Systems

Recent academic endeavours have explored various dimensions of AI in career guidance, particularly focusing on personalization and automation. Jadhav et al. [3] proposed an NLP-powered data-driven career decision chatbot tailored for Indian students. While effective in processing textual queries, the system remains fundamentally text-based and lacks comprehensive multilingual and conversational capabilities, which are essential for broader accessibility in diverse populations. The existing AI-driven career guidance systems—such as those by Avinash et al. [4], Birajdar et al. [5], and Arshad et al. [6]—demonstrate strengths in personalized recommendations, skill gap analysis, and conversational AI. However, they share common limitations: none fully integrate multimodal inputs like voice or hybrid interaction mechanisms, and multilingual support remains underdeveloped. These gaps highlight the need for a system that combines voice-enabled, hybrid, and linguistically inclusive interactions to enhance user engagement and accessibility. In contrast, the proposed framework is designed from the ground up to support multimodal interaction, combining both voice and text inputs, along with multilingual capabilities. By leveraging cloud-based speech recognition and synthesis technologies, the system ensures greater accessibility, inclusivity, and real-time interaction, addressing the limitations observed in prior academic

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works.

2.2. Comparison with Hosted Platforms

Beyond academic research, several industry-level platforms provide career guidance services, including Naukri Career Navigator [7], the National Career Service (NCS) Portal [8], and MyNextMove [9]. These platforms offer structured career information and basic recommendation features, making them widely accessible. However, they share common limitations that affect their overall effectiveness. Most platforms are predominantly text-based and rely on static workflows, limiting dynamic context understanding. They lack real-time conversational AI and emotion-aware features, leading to less personalized interactions Shown in Table 1.

Table 1 Comparison of AI-Powered Career Guidance Systems

Feature	CareerAI / MyNextMove	Naukri Navigator	Proposed Framework
Language Support (Voice)	English Only	English (Primary)	English, Hindi, Kannada
Input Modality	Text	Text	Voice & Text
Personalization Depth	Basic to Moderate	Moderate	High (Interests, Skills, Marks, Sentiment)
Emotion Awareness	No	No	Yes (VADER)
AI Explainability	Limited	No	Yes (Knowledge Graph)
Feedback / Refinement	No	No	Explicit (Q-Learning Loop)

3. Proposed Methodology

The proposed Intelligent Learning Framework is designed as a modular, multi-agent system that delivers personalized, multimodal, and multilingual career guidance. The architecture emphasizes scalability, adaptability, and efficient processing while maintaining a user-friendly interface. It integrates multiple intelligent components to analyze user inputs, interpret preferences, and generate accurate and context-aware career recommendations. The modular design also allows future enhancements without affecting the overall system stability.

3.1. System Architecture

The system follows a client-server architecture, structured into four major layers as illustrated in Figure 1. Each layer is responsible for a specific set of functionalities, ensuring clear separation of concerns and smooth data flow across the system. This layered design enhances modularity, making the system easier to develop, maintain, and scale. It also supports independent updates and efficient communication between components, thereby improving overall system performance and reliability.

- **User Experience Layer:** Developed using React.js, this layer provides an intuitive and responsive interface that supports both text and voice inputs. It enables users to interact seamlessly with the system, view personalized recommendations, and submit feedback for continuous improvement. The interface is designed to be accessible, user-friendly, and compatible across devices, ensuring a consistent user experience.
- **Application Integration Layer:** The backend is implemented using Flask, which acts as the central controller of the system. It manages communication between the user interface and the intelligent processing modules, handles request routing, processes

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input data, and ensures efficient response delivery.

- **Cognitive Processing Layer (Multi-Agent System):** This layer forms the core intelligence of the framework and consists of multiple specialized agents working collaboratively to deliver accurate recommendations.
- **Semantic Matcher:** Utilizes SBERT to generate embeddings and compute cosine similarity between user input and career data. This enables accurate semantic matching by capturing context and meaning beyond simple keyword comparison.

Emotion analyzer uses VADER sentiment analysis to detect user emotional tone, enabling the system to adapt recommendations based on sentiment and engagement. Rule-based engine uses IF–THEN rules to filter careers based on performance, skills, and preferences, ensuring valid and easily updatable recommendations. The adaptive agent uses Q-learning to adjust parameter weights dynamically, improving accuracy through continuous user feedback.

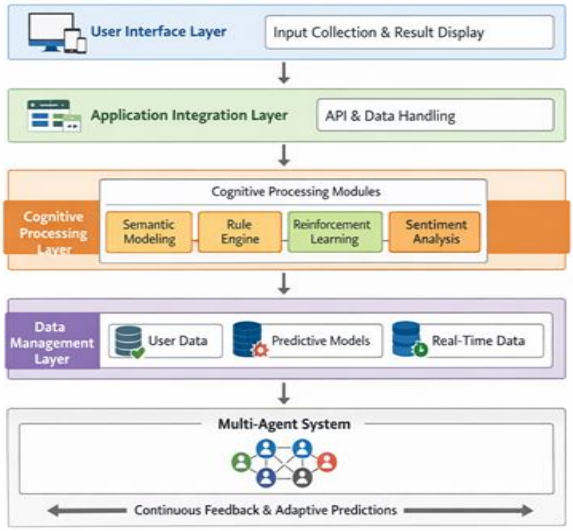

Figure 1 System Architecture — AI Career Guide welcome screen (Source: Project Presentation)

3.2. Core AI Logic

The core AI logic integrates several specialized modules to generate recommendations.

- **Semantic Matching Module (SBERT):** This module quantifies career relevance by understanding the contextual meaning of user input rather than relying on keyword matching. It uses Sentence-BERT (SBERT) with the 'all-MiniLM-L6-v2' model to generate embeddings for user profiles and career descriptions, and computes cosine similarity to measure their relevance and alignment. This improves the accuracy and robustness of recommendations.
- **Rule-Based Reasoning & Adaptive Fusion:** A Rule-Based Engine applies deterministic constraints (e.g., "IF Mathematics > 85 THEN consider Engineering"). An RL layer (Q-Learning, α=0.1, γ=0.9) dynamically adjusts weights using user feedback (positive/negative reward) to personalize recommendations.
- **Emotion Analysis (VADER):** Real-time sentiment detection using VADER generates a compound score. Non-English inputs (e.g., Hindi, Kannada) are translated first, enabling empathetic, context-aware responses.
- **Knowledge Graph Module:** Built with NetworkX, nodes represent careers, skills, subjects, and traits; edges define relationships. It enables related career discovery and visual explainability of recommendations.

4. Implementation Plan

The framework is developed through a structured, phased approach for robustness. It uses Flask backend, MySQL/PostgreSQL database, and HTML/CSS/JS frontend Shown in Table 2.

Table 2 Implementation Plan Phases

Phase	Description	Key Activities
1	Requirement Analysis	Study base research, define scope, design hybrid AI framework.
2	Frontend Development	Develop UI for input collection, result display, and feedback mechanism.

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3	Backend Development	Set up Flask server, API endpoints, and database connectivity.
4	AI Module Integration	Implement SBERT, Rule Engine, RL (Q-Learning), and VADER modules.
5	Database & Data Setup	Configure PostgreSQL, store user data, career repository, and logs.
6	Testing & Evaluation	Perform functional testing, validate optimize latency.

5. Experimental Setup

To assess the effectiveness of the proposed Intelligent Learning Framework in delivering personalized career recommendations, a structured experimental evaluation was performed. This section details the dataset characteristics, baseline models, evaluation metrics, and validation procedures employed.

5.1. Dataset and Cohort Composition

The evaluation used a consistent dataset and 160 participants. The career repository was expanded to 85 career categories with over 510 skill mappings, as shown in Table 3. The 160 diverse user profiles were created via stratified sampling from urban, semi-urban, and rural backgrounds. Model accuracy was validated against a Curated Ground Truth (CGT) dataset from government and industry standards, with each career entry including skills, subjects, traits, salary, outlook, education, and work environment.

Table 3 Core Career Repository Characteristics

Metrics	Value
Number of Career Categories	85
Number of Unique Keywords	510+
Size of Raw Data (Characters)	58,100
Number of User Profiles Tested	160
Number of Survey Participants	160

5.2. Baseline Models for Comparison

To isolate the contributions of each architectural component and validate the superiority of the proposed hybrid framework, a comparative evaluation was performed against two baseline models:

- **Rule-Only Model (Baseline A):** This model uses only the deterministic rule-based reasoning engine to generate recommendations. It applies handcrafted IF-THEN rules based on eligibility constraints but lacks semantic understanding and adaptive learning.
- **SBERT-Only Model (Baseline B):** This model uses only the semantic matching module, employing Sentence-BERT embeddings to calculate cosine similarity between user responses and career profile descriptions. It lacks deterministic filters and adaptive refinement.

5.3. Evaluation Metrics

The following metrics were defined to quantitatively assess system performance:

- **Top-N Hit Rate:** The proportion of test profiles for which the correct target career appears within the system's top N recommendations. The Top-3 Hit Rate is reported as the representative indicator.
- **User Satisfaction Score:** A subjective metric collected through a post-interaction survey where participants rated their experience on a scale of 1 to 5 across dimensions including recommendation relevance, ease of interaction, clarity of information, and overall satisfaction.
- **System Latency:** The total end-to-end response time measured from user input submission to the display of recommendations, encompassing all intermediate processes.

5.4. Validation Procedure

To ensure statistical robustness: (1) CGT dataset comprised 160 evaluation profiles; (2) Key performance indicators presented with 95% confidence intervals; (3) User feedback systematically collected to train the Q-Learning

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agent.

6. Results and Analysis

This section presents a comprehensive evaluation of the proposed Intelligent Learning Framework, focusing on key performance indicators that demonstrate its accuracy, efficiency, and overall user experience. The evaluation methodology includes quantitative measurements of system responsiveness, qualitative assessments of recommendation quality through ablation studies, and user feedback analysis. All experiments were conducted using the 160-profile Curated Ground Truth (CGT) dataset described in Section V, with statistical significance evaluated at $p < 0.05$ using paired two-sample t-tests.

6.1. Core Recommendation Accuracy (Ablation Study)

A systematic ablation study was conducted starting from two baseline configurations (Rule-Only and SBERT-Only), incrementally adding modules to measure their impact. The complete proposed hybrid model (Configuration F) integrates all modules including the Reinforcement Learning feedback loop Shown in Table 4.

Table 4 Ablation Study Results (Top-N Hit Rates & User Satisfaction)

Config.	Modules Active	Top-1 (%)	Top-3 (%)	User Sat. (/5)
A	Rule Only	52.5	74.0	3.60
B	SBERT Only	64.4	86.0	4.10
C	Rule + SBERT	68.1	88.5	4.35
D	+ VADER (Emotion)	71.3	89.4	4.49
E	+ Knowledge Graph	76.7	90.3	4.66
F	+ RL Feedback (Full)	77.5	90.5	4.71

6.1.1. Key Observations from Table 4

The complete hybrid model (Config. F) significantly outperformed baselines ($p < 0.01$). Adding Knowledge Graph and RL Feedback increased Top-1 Hit Rate from 71.3% to 77.5%, proving structured reasoning and adaptive learning are crucial for precision.

6.2. User Satisfaction Analysis

Among 160 participants, the framework achieved a mean satisfaction score of 4.71/5.0 (95% CI: [4.58, 4.77]). Key findings: 88% found recommendations "very relevant"; 92% positive for voice/text interface; 85% found Knowledge Graph helpful. Figure 2 shows consistently high scores across all parameters, with ease of interaction rated highest.

6.3. System Latency & Performance

Figure 3 shows voice input averages 0.30–0.38 sec (including STT), while text input averages 0.18–0.20 sec, ensuring responsive user experience Shown in Table 5.

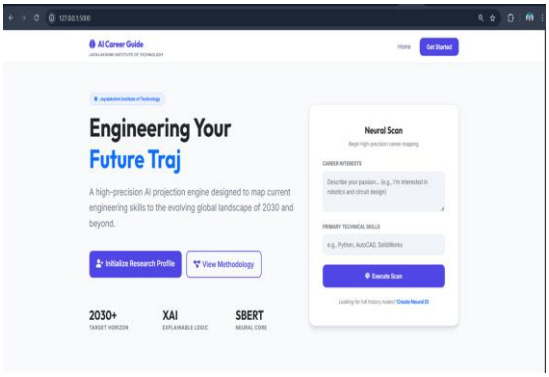

Figure 2 User Satisfaction Scores Across Different Evaluation Parameters

Table 5 Latency Breakdown Across Operating Conditions

Component	Condition	Mean ± SD (ms)
Recommendation Engine	Optimal	350 ± 45
Recommendation Engine	Low Bandwidth	365 ± 50
Cloud API (STT/TTS)	Optimal	550 ± 70
Cloud API (STT/TTS)	Low Bandwidth	800 ± 120
Frontend Rendering	All	50 ± 15
E2E Response	Optimal	1000 ± 95
E2E Response	Low Bandwidth	1765 ± 150

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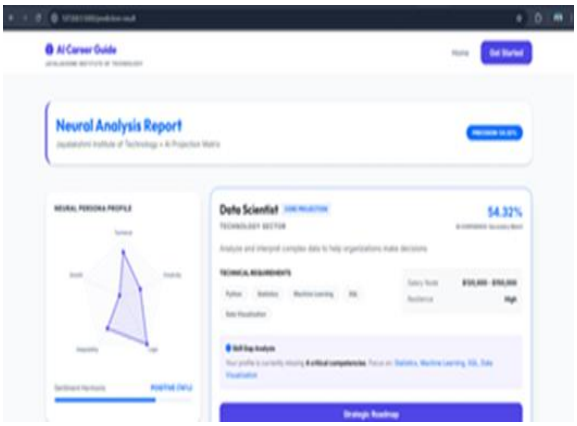

Figure 3 Neural Analysis Report Showing Data Scientist Recommendation, Skill Gaps, Sentiment Score, and Salary Projection

6.4. Multilingual Consistency and Cross-Language Performance

To address potential performance variances between languages, core NLP components were evaluated on a balanced test set (N=160) across the three supported languages.

6.5. Database-Driven Analysis and Feedback Integration

All user interactions and system outputs were logged in the MySQL database. Analysis revealed that 91% of users expressed satisfaction with the platform and its career predictions, validating the strength of the hybrid recommendation framework.

7. Discussion

The Sankalp-inspired Intelligent Learning Framework demonstrates a compelling fusion of multi-agent reasoning, rule-based logic, and semantic intelligence to provide personalized career guidance that is accessible, contextually aware, and emotionally responsive. The ablation study shows SBERT alone achieves 86.0% Top-3 Hit Rate and rules alone 74.0%, but their combination with Knowledge Graph and RL yields 90.5%. The Q-Learning agent (α=0.1, γ=0.9) dynamically adjusts recommendation weights based on user feedback, enabling true adaptivity. The VADER module detects emotional tones like confusion or enthusiasm and adapts responses accordingly. This contributed to the high user satisfaction score of 4.71/5.0. Overall, hybrid integration of semantic, rule-based, and adaptive learning delivers superior performance Shown in Table 6.

7.1. Comparative Analysis with Existing Systems

Table 6 Comparison of Proposed Framework with Existing Systems

Aspect	LLMs (GPT-4, PaLM)	Traditional Rule-Based	Proposed Hybrid Framework
Reasoning	Probabilistic pattern matching	Deterministic IF-THEN rules	Hybrid: Rules + RL-based adaptivity
Explainability	Limited, opaque outputs	Transparent but rigid	Transparent via Knowledge Graph
Constraint Handling	Weak logical enforcement	Strong but inflexible	Deterministic rule-based validation
Adaptivity	Needs fine-tuning	None	RL-driven feedback refinement
Emotion Awareness	Limited	No	Yes (VADER)

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Multilingual Support	Broad, often inconsistent	Rare	English, Hindi, Kannada (TTS/STT)
Latency	High (1–5 s)	Low (50–100 ms)	Efficient (350 ms core)

7.2. Current Limitations

Despite the robust architecture, challenges persist: (1) Rule-model rigidity in edge cases may overly constrain personalization; (2) Translation dependency for sentiment analysis introduces a minor accuracy drop (~5%) for Hindi/Kannada; (3) Dependency on cloud APIs introduces network dependency and recurring costs; (4) Limited external validation requires formal expert panel evaluation.

7.3. Ethical Considerations and Responsible AI

The framework incorporates fairness and bias mitigation through multilingual SBERT embeddings, privacy and data protection via encrypted MySQL storage, and user autonomy through accept/reject feedback mechanisms.

8. Future Work

Future work will focus on: (A) Formal expert validation using Cohen's Kappa for inter-rater reliability; (B) Advanced adaptability through integration with GPT or PaLM for deeper causal reasoning; (C) Mobile application deployment using React Native with offline mode; (D) Gamified interaction layer with career quizzes and mission-style roadmaps; (E) Expanded multilingual support for Tamil, Telugu, Marathi, and Bengali; (F) Integration with real-time labor market APIs.

Conclusion

This paper presented an Intelligent Learning Framework for predictive modeling in AI-driven career guidance. By integrating deterministic rule-based reasoning with dynamic semantic understanding (via Sentence-BERT) and enhancing adaptability through Reinforcement Learning (Q-Learning), the framework offers a highly personalized, accessible, and explainable guidance experience. Key contributions include: (1) A modular, multi-agent hybrid architecture; (2) Multimodal and multilingual interaction supporting voice and text across English, Hindi, and Kannada; (3) Emotion-aware interaction through VADER sentiment analysis; (4) Explainable AI through an integrated Knowledge Graph. Experimental results validated against a CGT dataset of 160 user profiles demonstrated: Top-1 Hit Rate of 77.5%, Top-3 Hit Rate of 90.5% (95% CI: [88.1%, 92.9%]), and Mean User Satisfaction Score of 4.71/5.0 (95% CI: [4.58, 4.77]). Operational analysis confirmed efficient core logic with mean latency of 350 ms. The framework successfully addresses critical barriers including shortage of trained counsellors, lack of personalization, language diversity challenges, and limited accessibility, aligning with India's NEP 2020 and UN SDG 4 and SDG 8.

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